Introduction

I developed an algorithm to calculate numerical learning gains based on skills (Skill Points [®]). To take this to the next generation (2.0), improve the algorithm to include a coefficient (growth rate) for each skill (on a skill by skill basis). I started to think how to accomplish this and below are some of the seed ideas. The assumption is we are using the patent pending learning labels technology as a standard representation of learning expectations for tasks or experiences – where Skill Points[®] are derived.



Hypothetical Learning Curves for Selected Skills

Time, Level of Difficulty, Quality of Learning www.skillslabel.com | www.educationlabel.com | www.learninglabel.com

Why Skills Points?

I think of Skill Points as a competency as a measurement of skill – a numerical learning gain. Calculate the sum of Skill Points to understand a level of achievement for a learner, what learning is taking place in a program – course, curriculum, onboarding, or training program, and what is required for a job or profession.

I use the analogy skills are used to define learning and job requirements like atoms are used to define substances. I agree we need to get deeper by also tracking the underlying methods and applications of skills.

Skill Points work across education, higher education, and professional development – effectively bridging them together. Part of the learning labels system is the create an emblem – a dynamic learning badge that sum Skill Points, number of tasks, and number of hours. Imagine of sharing a collection of skills emblems (representing all the skills in your skill set) along with an e-portfolio.

How do we create growth rates for skills?

Time longitude study (analogous to taking the CLA+ before and after college)ⁱ. Track learning in skills (methods and applications and standards) with a collection of users through time. The groups should

represent different stages of learners (education, higher education, and professional development). Take periodic assessments. Aggregate the results. *Construct coefficients based on the results.*

Use current curriculum and credit hour system. Define current learning plans and curriculum in skills (methods and applications and standards). Use current credit hour system and other ways to measure progress. *Construct coefficients based on time, skill, and achieving skills levels*.

Use human learning starting from scratch. Use -pre, -during, and -post assessments to measure how a learner improves in learning skills in a task or experience. Aggregate the results: *match skill to time, level of difficult, and type (quality) of the learning experience.*

Use machine learning / AI starting from scratch. Use -pre, -during, and -post assessments to measure how a system improves in learning skills in a simulated task or experience. Take the results: *match skill to time, level of difficult, and type (quality) of the learning experience.*

These methods are not mutually exclusive. The advantage of the first two methods is they can be started right away. For the longitude study, start once the study is designed. For the curriculum mapping, start mapping a curriculum or learning program. The last two methods require a database of learning labels and the 'human learning idea' requires a healthy number of users in the system.

My recommendation is to start the first two methods. Build a longitude study for the basic thinking and soft skills; identify students and implement the study (expecting to see results covering a few years). Start mapping curriculum to skills using the learning labels technology. Use the results to get competencies based on the traditional higher education credit hour system (something we want to move away from, but gradually). A benefit of this mapping skills to learning is it also applies to mapping skills to jobs and professions.

The idea of numerical learning gains (Skill Points[®]) is a compelling feature of the learning labels technology. Building them through education, higher education, and a career connects these stages together. The results of this study – skill coefficients – will be immediately plugged into the Skill Points[®] algorithm.

Skill Dimensions

Understand attributes in defining skills and how they relate to each other. This is particularly relevant as we use skills to track learning through time and match skill maps to learning programs. Consider the following table:

ROOT SKILL	SYNONYMOUS	RELATED SKILLS	METHODS
PROGRAMMING	Coding	Python, Javascript, C#	File Management, Object oriented programming
VERBAL COMMUNICATION	Speaking	Presenting, Listening	Conversations, Meetings
WRITTEN COMMUNICATION	Writing	Report Writing, Grant Writing	Composition, Grammar
WEBSITE DEVELOPMENT		HTML, CSS, JQuery	Architecture, Client side Interaction, Server side Interaction

CRITICAL THINKING	Problem Solving,	Induction, deduction,
	Reasoning	summarization, ranking,
		sense making

For tracking purposes, it is worth marking root skills with synonymous skills in a database (skills that can be replaced with each other). The solution is simple. A learning practitioner puts either 'programming' or 'coding' on a learning label – either representation. On a Skills Emblem (dynamic badge), a skills map, or other summarization, use only the root skill and summing both representations together with Skill Points.

Rather than show a learner accumulated 100 Skill Points [®] in **Coding** and 200 Skill Points [®] in **Programming** from learning labels, say a learner accumulated 300 Skill Points [®] in **Programming**.

Root skills and related skills should be treated as separate line items. This is how they appear on a learning label. This is how they appear in a LinkedIn profile. Though, it is worth understanding the relationship between a root skill and related skills.

For example, a college graduate is taught to program and might learn a few related skills – programming languages. When applying for jobs, the skill of programming is valuable regardless of the required language. How do we allocate proper attribution between what might be considered a transferable skill with a technical skill – a 'sub-skill'?

Once there is a large data set of learning labels to work with, understand how skills cluster together.

Methods are not 'related skills' but are worth tracking. For example, the paramount skill of critical thinking is too difficult to track by itself, so makes sense to track the methods and frameworks behind applying the skill. Education and training standards are largely a representation of methods. The above-mentioned relationship of a root skill and its synonymous skills is also important in matching standards to skills.



Consider the following Skills Map for an early stage Web Developer:

Programming should be interchangeable with coding. On a Skills Emblem, resume, portfolio, personal website, or LinkedIn profile, a substitution should be made automatically.

Critical thinking should be included, but a reference to the related methods tightens the map.

Does the programming requirement include Javascript, HTML, CSS, and SQL? How do we negotiate differences in required languages (i.e. experience in Python, Java, etc.)?

With the second generation of Skill Points, I would like work on these inconsistencies with skills for tracking lifelong learning.

Academically Adrift. Book includes study of college students taking the CLA+ at different stages in higher education.